A Convolutional Neural Network for Removing GOES-17 Image Anomalies to Improve CERES Broadband Flux Measurement

Benjamin Scarino[1], David R. Doelling[2], William L. Smith Jr.[2], Michele Nordeen[1], and Pamela Mlynczak[1]

1. Science Systems and Application, Inc., Hampton, VA, USA

2. NASA Langley Research Center, Hampton, VA, USA

Background

CERES provides satellite-based global climate data record of Earth's radiation budget and clouds

CERES = Clouds and the Earth's Radiant Energy System

Measurement anomalies impact cloud retrieval

Incorrect Cloud Phase = Incorrect Flux

Unmitigated bad scanlines will impact climate data records

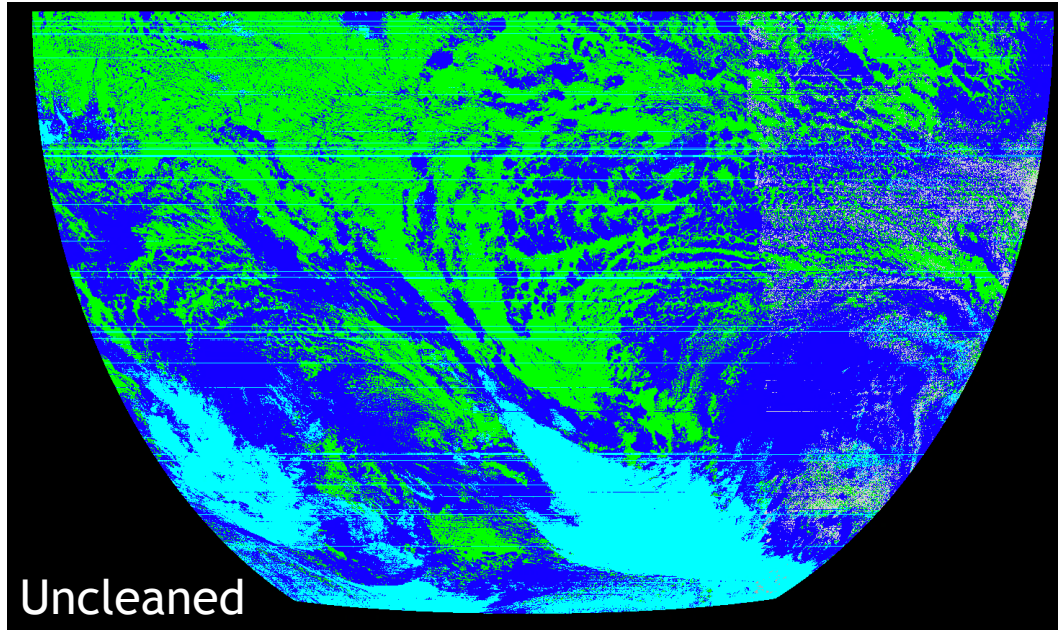GOES-17 ABI cooling system anomaly = many bad scanlines at night (~10:30–16:30 UTC)

Cleaning imagery of bad scanlines is laborious but necessary

A convolution neural network (CNN) can identify and clean bad scanlines as effectively as a human

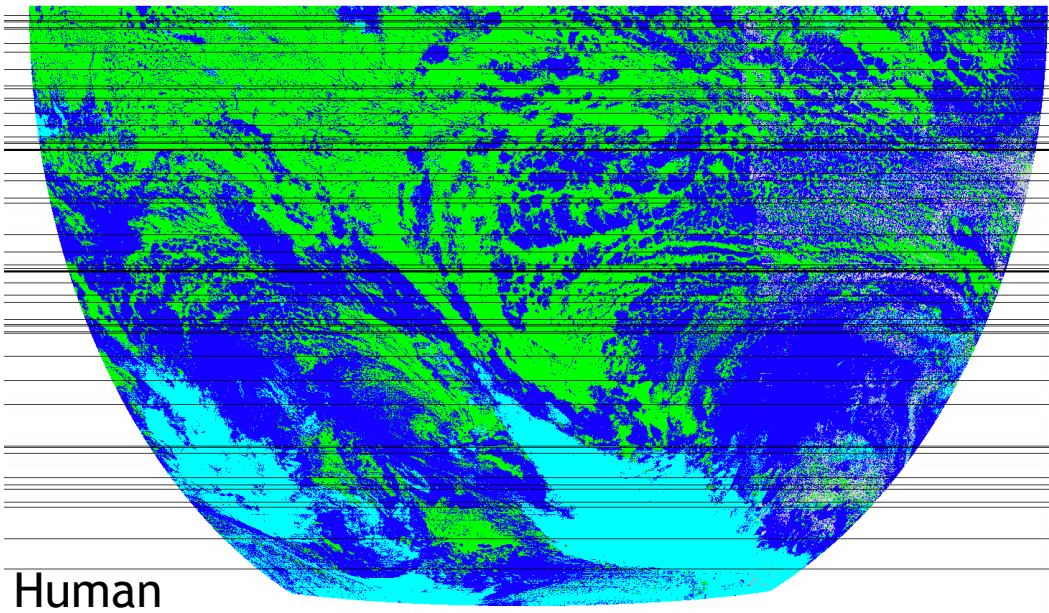

CERES Ed4 GOES-17 Cloud Phase: 29 Aug 2021, 14:30 UTC

Ice
Liquid
Clear
Suspected Cloud
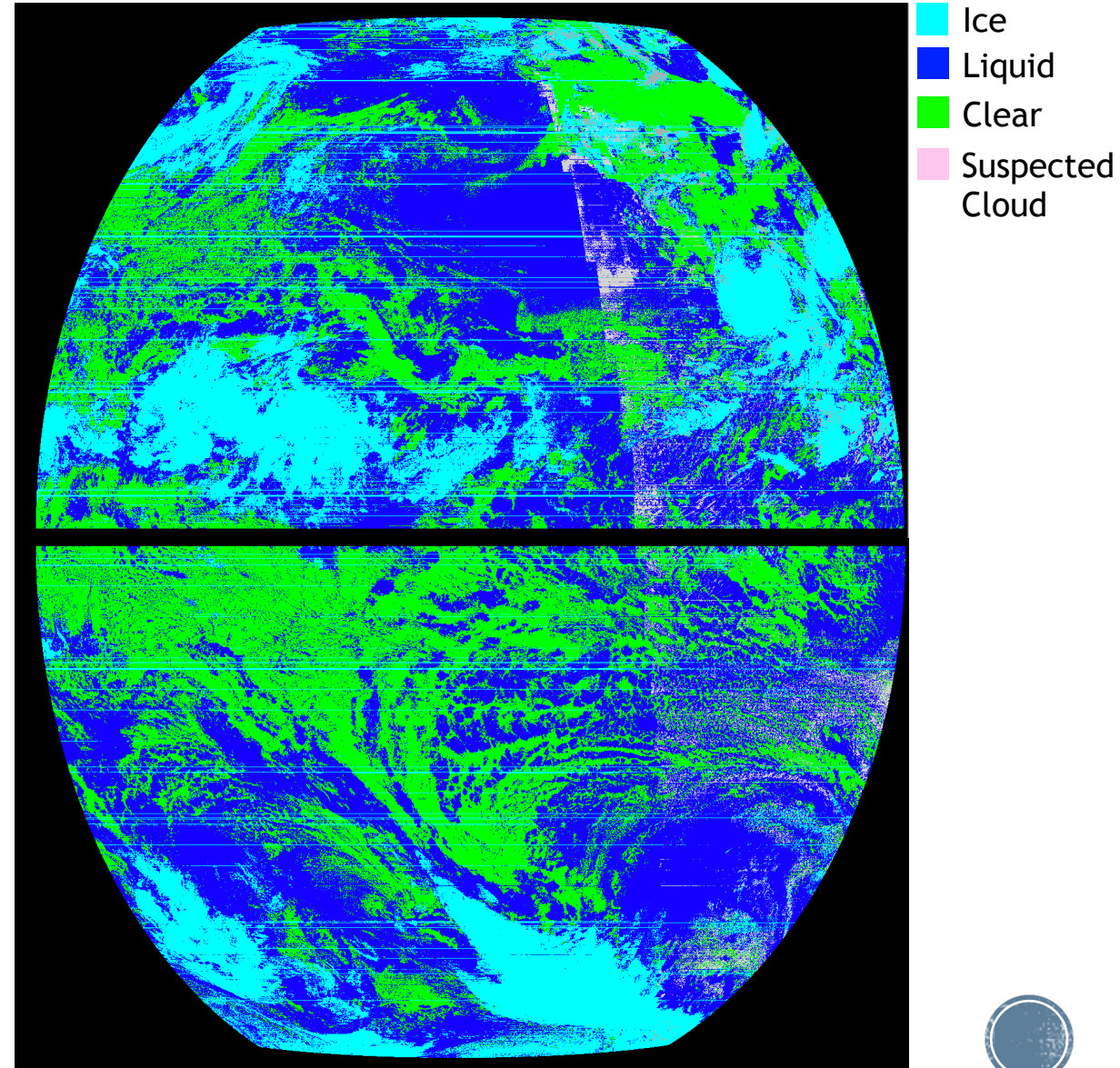
Motivation for CNN

Phase:
- Ice
- Liquid
- Clear
- Suspected Cloud

Uncleaned

Human
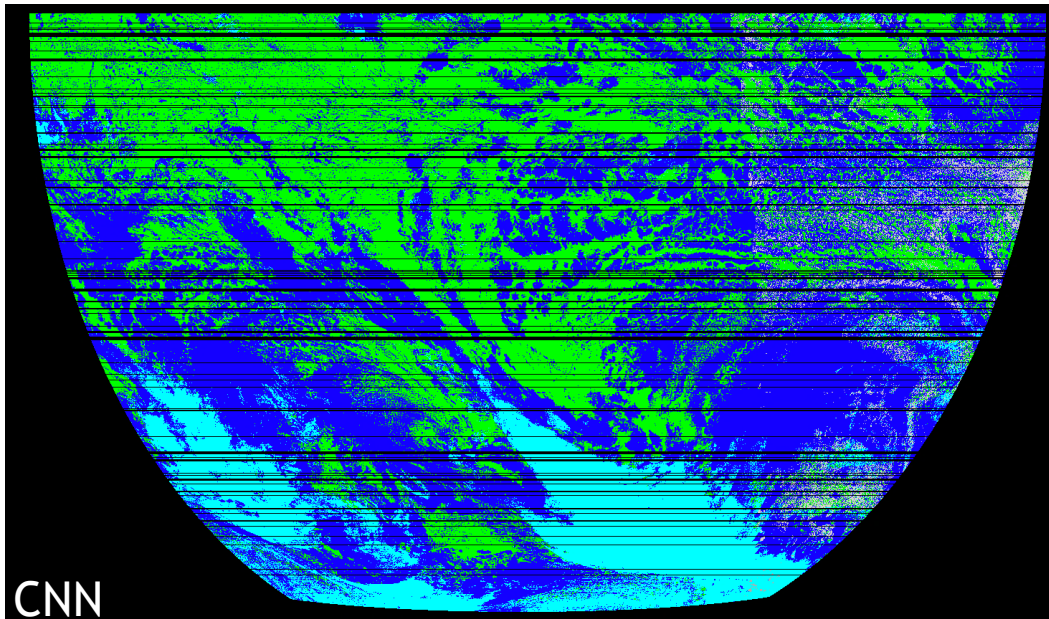
CNN

Bad scanlines evident by unnatural cloud phase stripes above

Human and CNN cleaning are comparable

CNN cleaning is fast, easy, and more comprehensive

CNN Approach
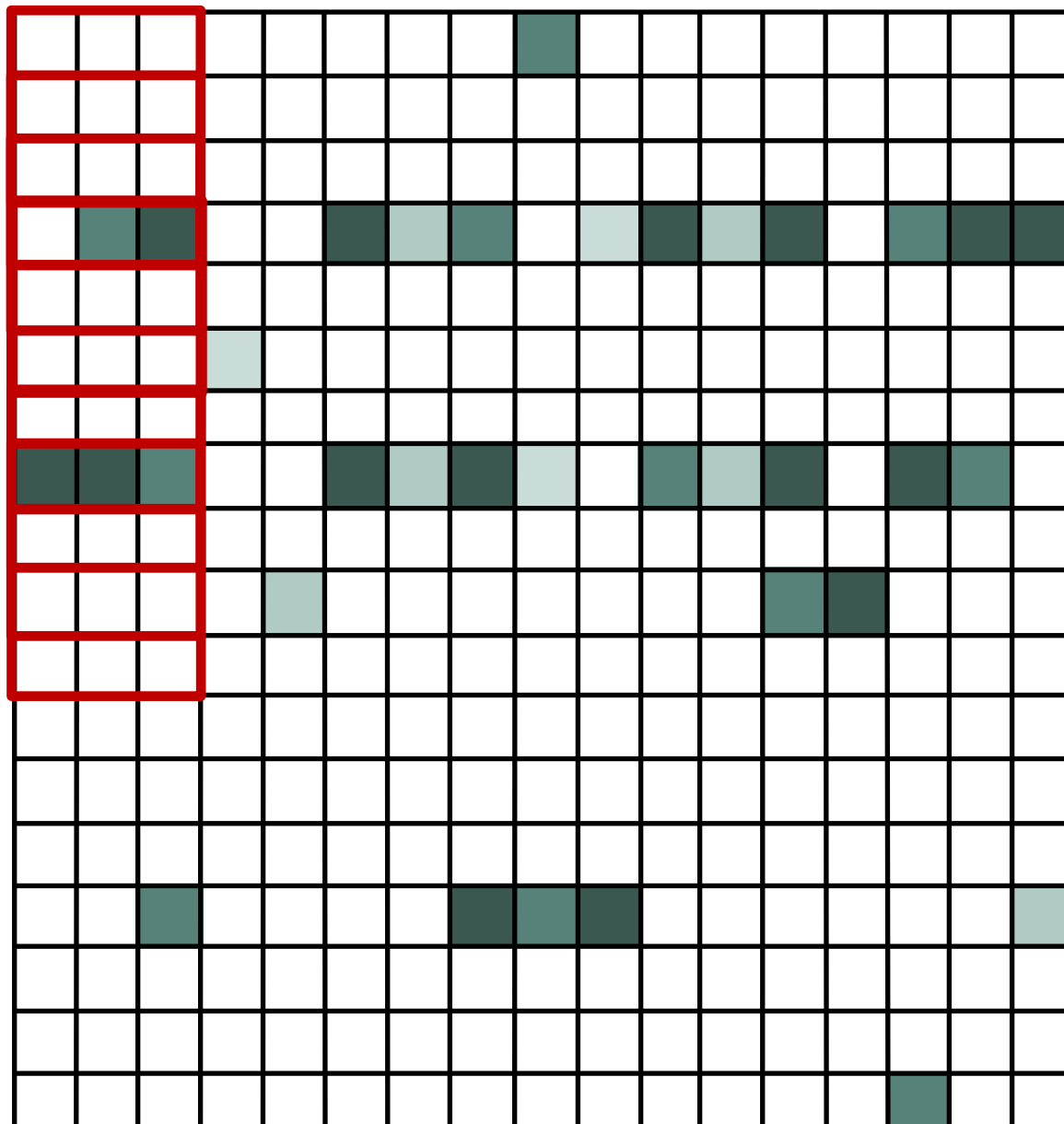

Conceptual satellite imagery →

White = normal appearing
Green = some degree of visual anomaly

CNN identifies and removes (cleans) the anomalous scanlines

Anomalies more apparent in certain products/channels

Scan each line and decide whether it needs cleaning

Decision based on center row of the 3x3 scan filter

→ $\hat{y}=0$
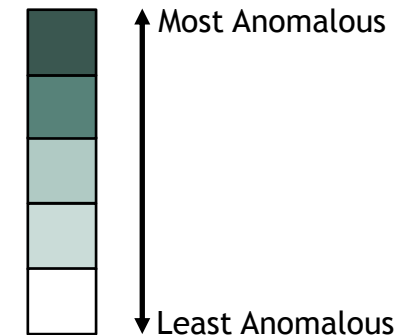→ $\hat{y}=0$
→ $\hat{y}=0$
→ $\hat{y}=1$
→ $\hat{y}=0$
→ $\hat{y}=0$
→ $\hat{y}=0$
→ $\hat{y}=1$
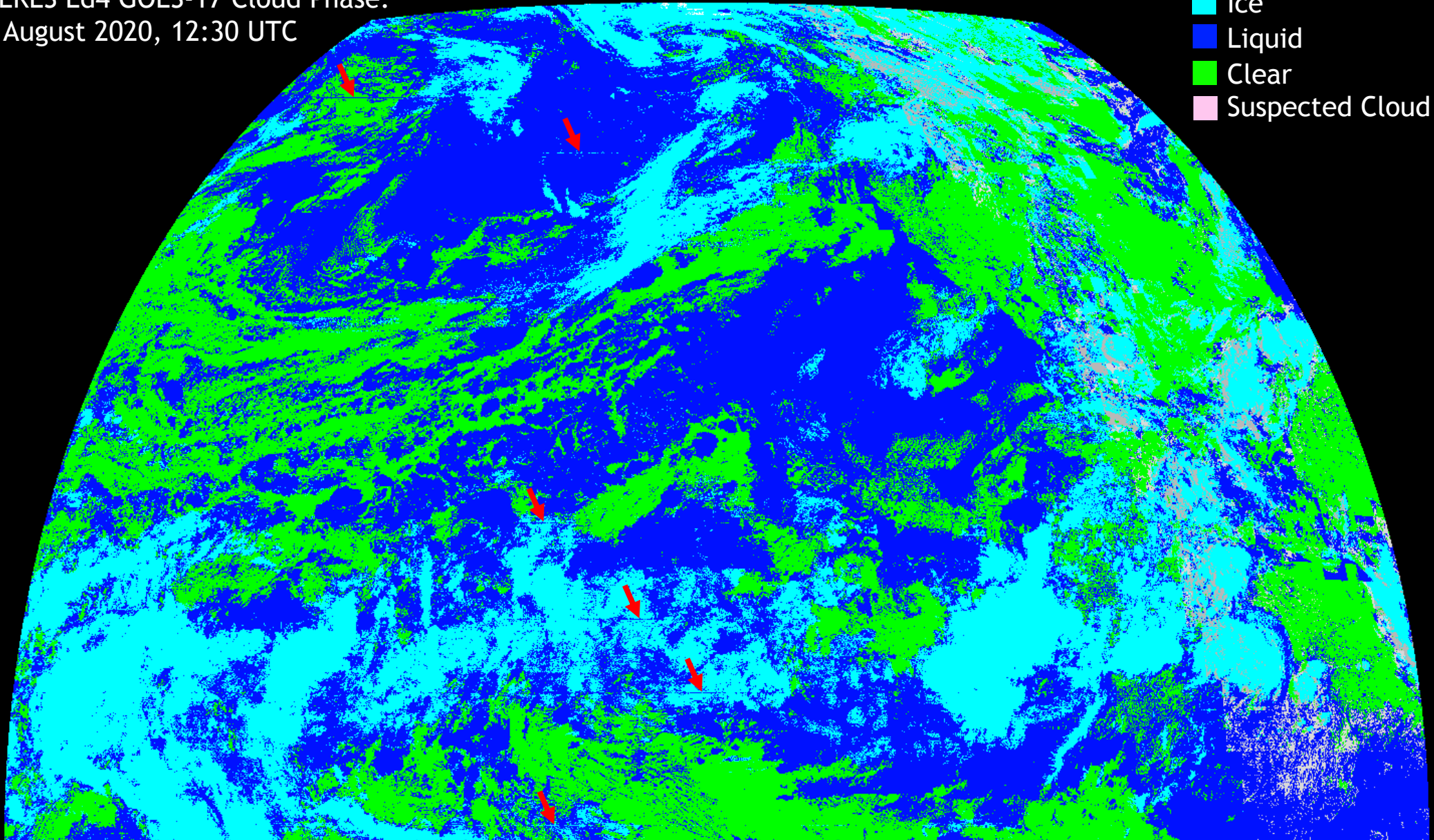→ $\hat{y}=0$
→ $\hat{y}=?$

Most Anomalous

Least Anomalous

How does the CNN learn to make these judgements?

Curating a Dataset

CERES Ed4 GOES-17 Cloud Phase:
1 August 2020, 12:30 UTC
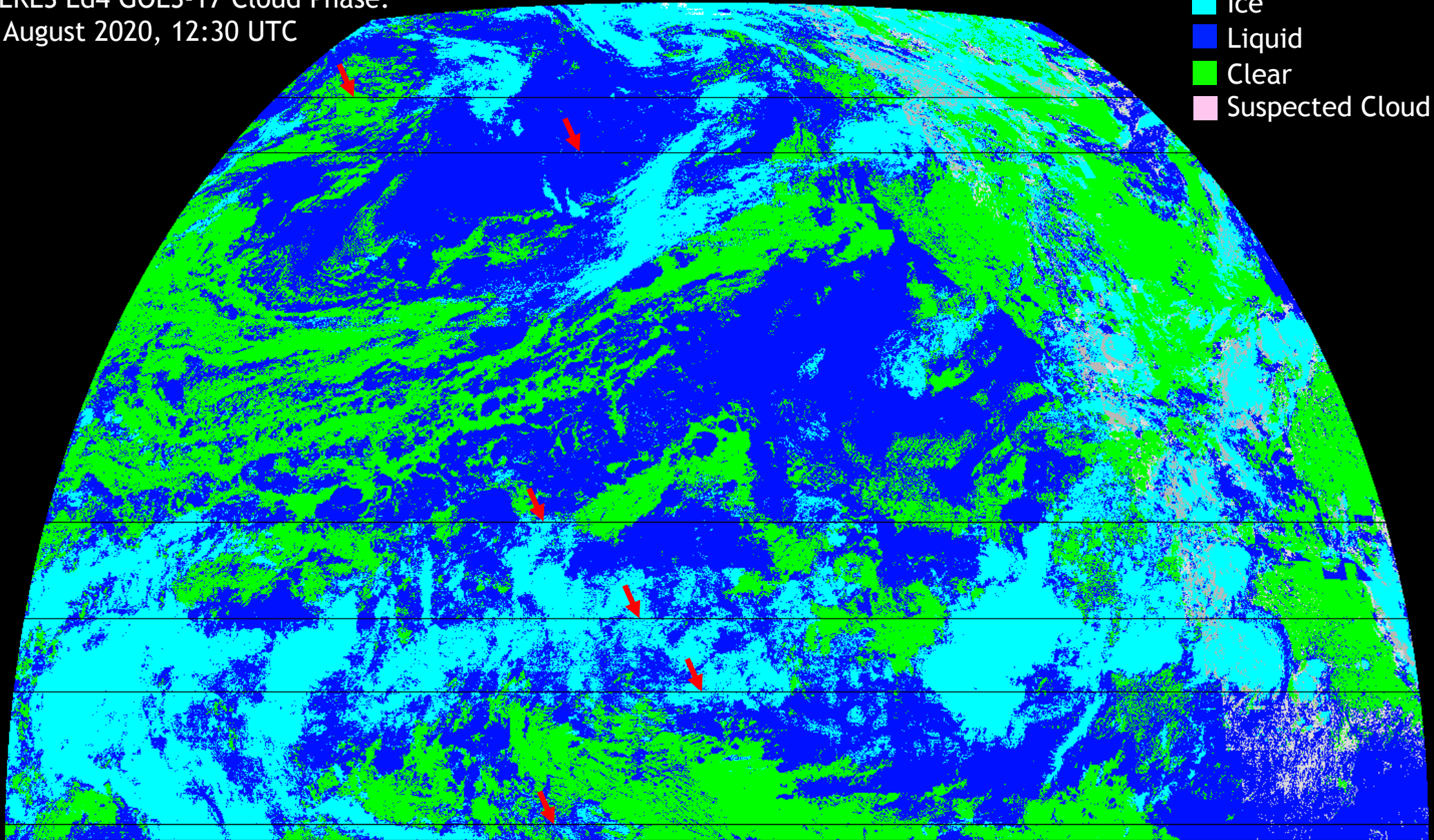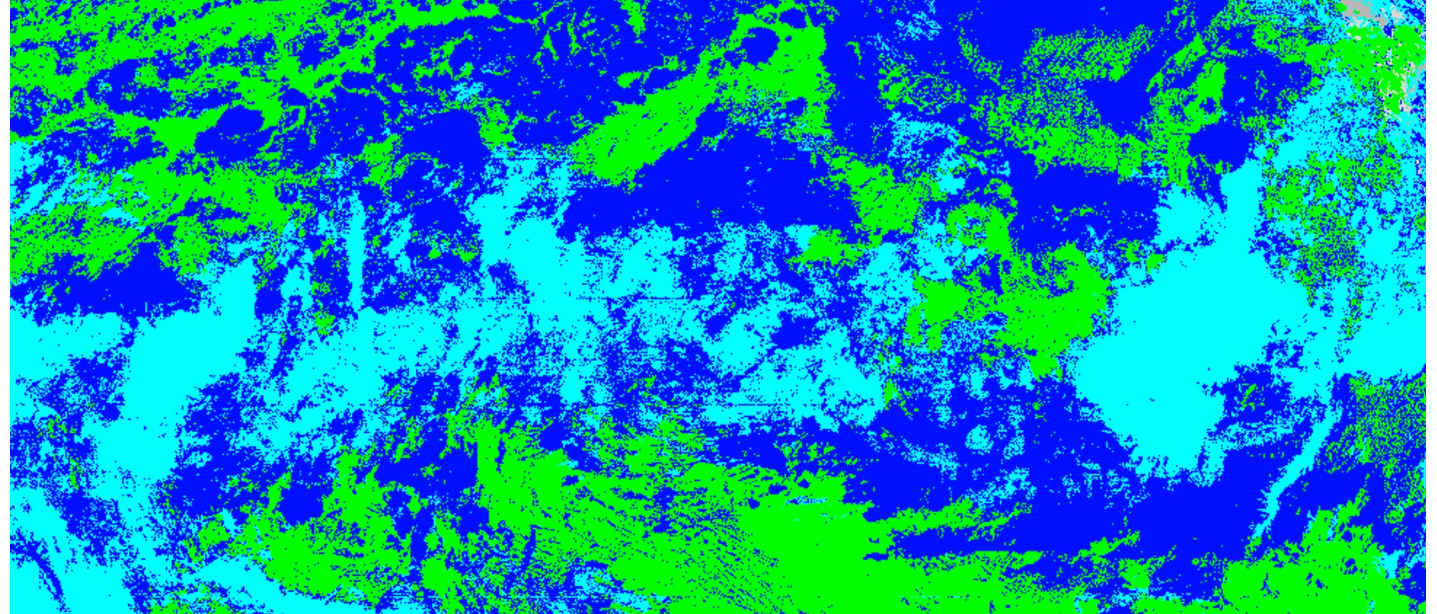
Ice
Liquid
Clear
Suspected Cloud

Curating a Dataset

CERES Ed4 GOES-17 Cloud Phase:
1 August 2020, 12:30 UTC

Ice
Liquid
Clear
Suspected Cloud

Curating a Dataset

Scrutinize hundreds of CERES product files

1 Aug – 7 Sep 2020
10:30 – 16:30 UTC hourly

➡️

Manually select scanlines for cleaning given best judgment of channel/product data

1) Cloud Phase
2) 3.9–11-µm BT Difference (greatest contrast)

This approach now replaced by the CNN

Time consuming, Unreliable, Inconsistent, ★Eye straining★

Training the CNN

Extract cleaned subsets with dimension 3xN

Select such that center line is one that has been manually cleaned
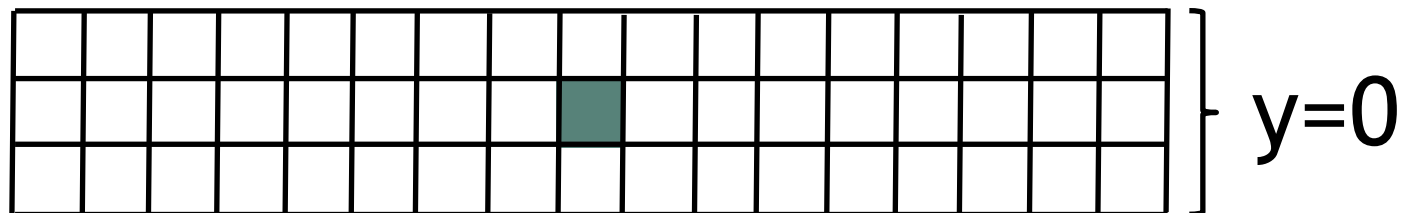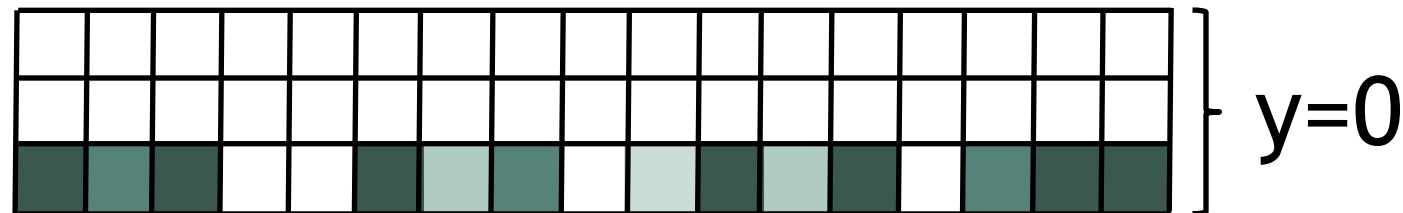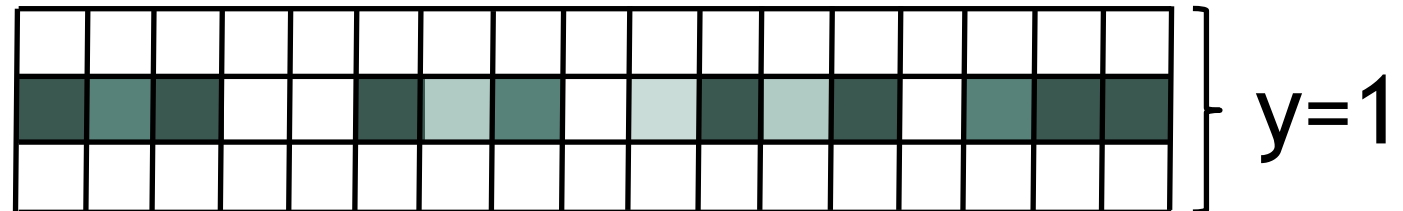
Save as "true" class

Augment "true" class, i.e., 4x the samples by flipping 3xN vertically and horizontally

Randomly selected equal amount of uncleaned subset

I.E., center line not cleaned

Save as "null" class

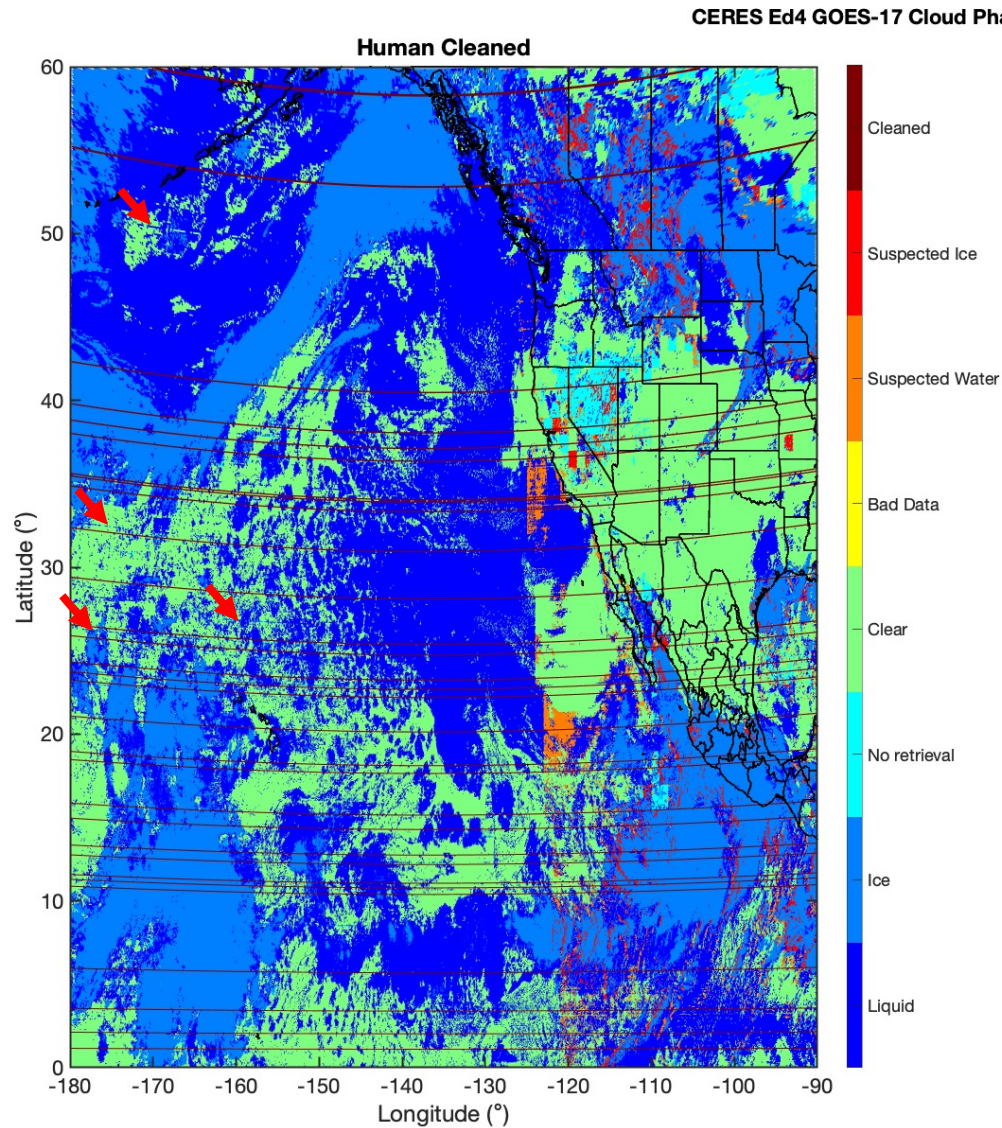**Also save corresponding predictors**

y=1

y=0

y=0

Validation Set Metrics	
Recall	82%
False Alarm Ratio	38%
False Alarm Rate	1%

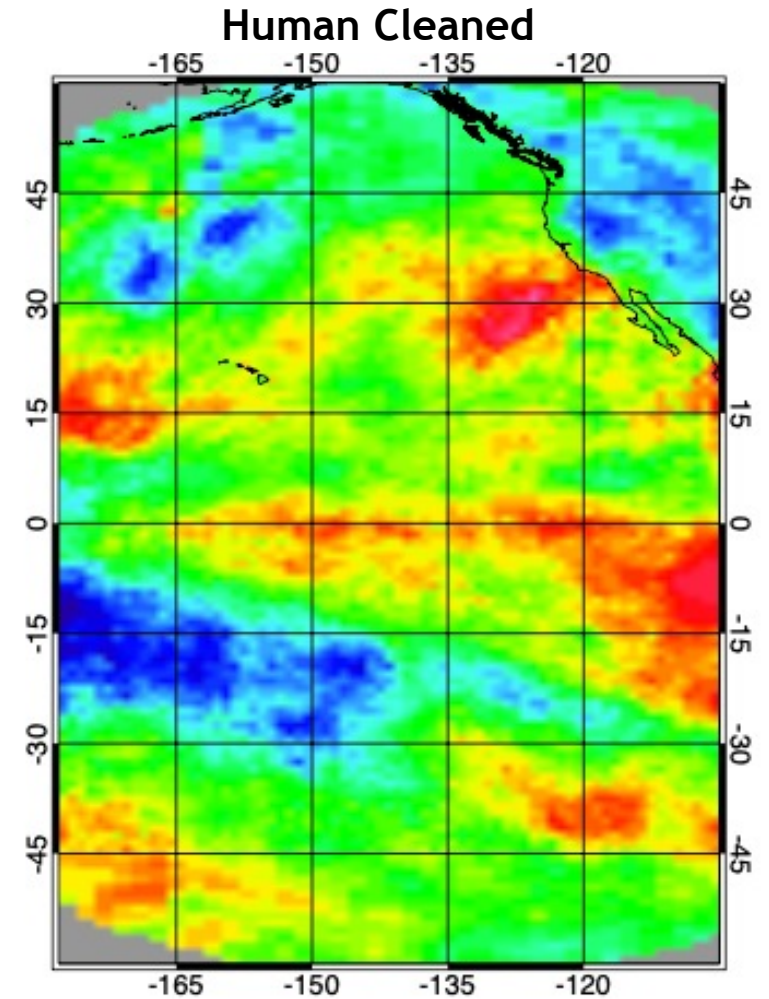Training set isn't perfect because a human isn't perfect

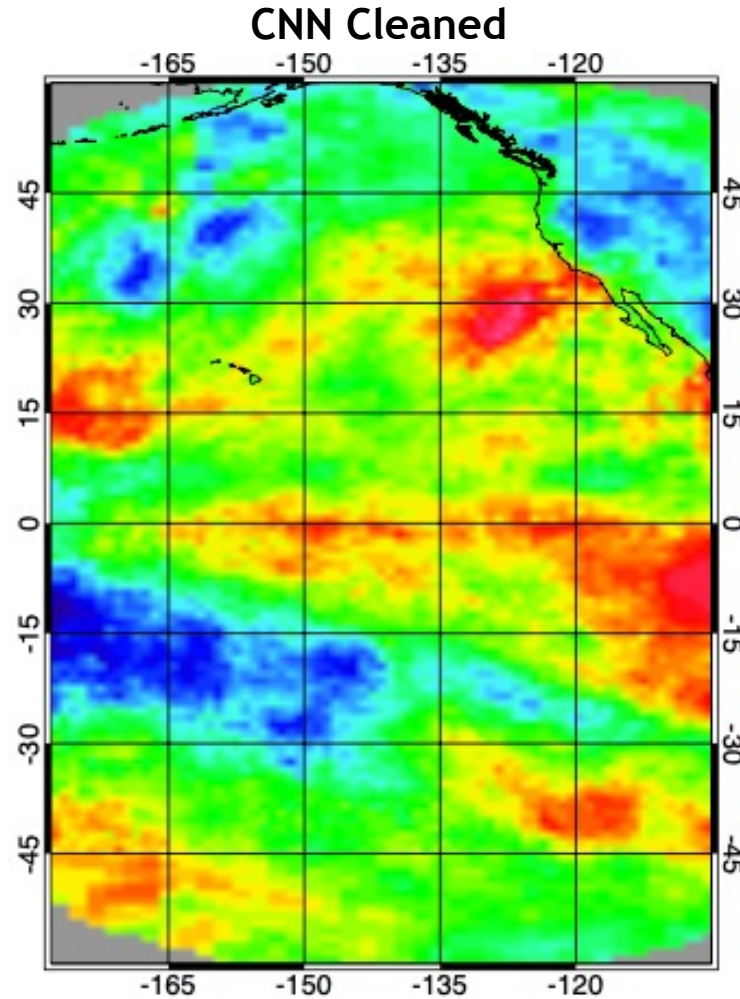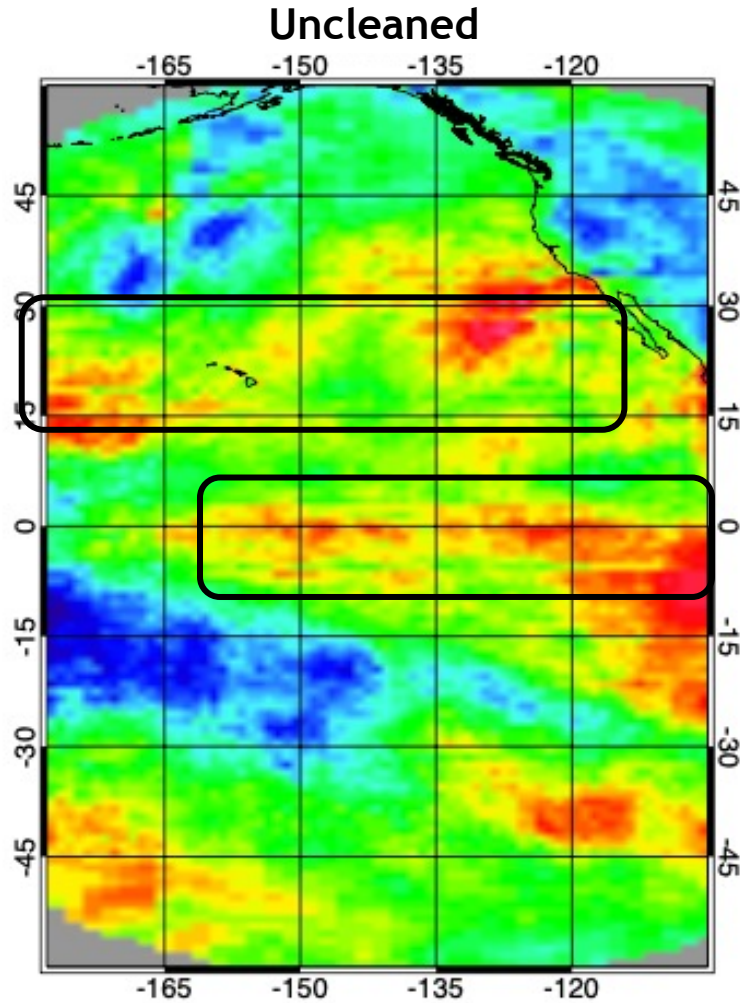Metric for success = is the CNN at least as consistent as a human?

CNN vs. Human Cleaning

CERES Ed4 GOES-17 Cloud Phase: 2021 239 14:30 UTC

Human Cleaned

Feb 2021 Cloud Top Pressure: 13:30 UTC Average

Uncleaned

CNN Cleaned

Human Cleaned

hPa

Regional Differences: Cloud Top Pressure and Temperature

CNN Cleaned – Uncleaned · CNN Cleaned – Human Cleaned · CNN Cleaned – Uncleaned · CNN Cleaned – Human Cleaned

Bias 5.33 — Sigma 10.59 — hPa

Bias 0.93 — Sigma 3.79 — hPa

Bias 0.59 — Sigma 1.20 — K

Bias 0.10 — Sigma 0.42 — K
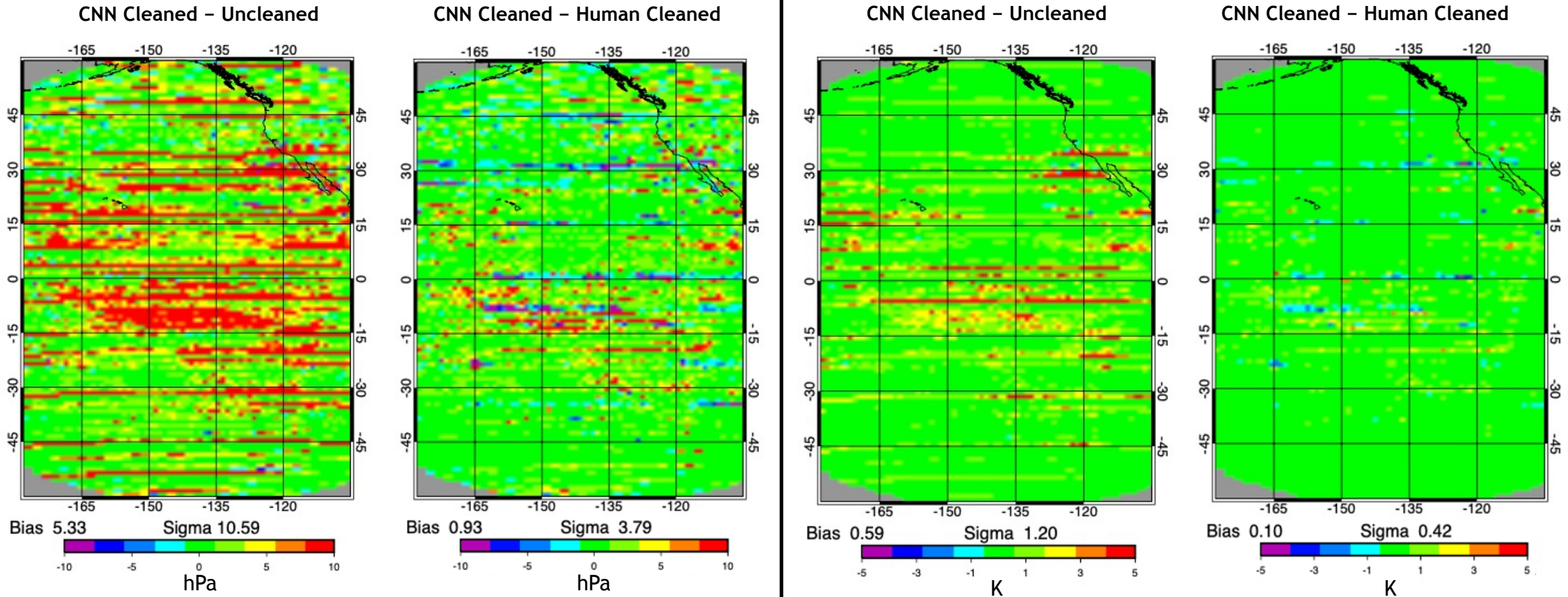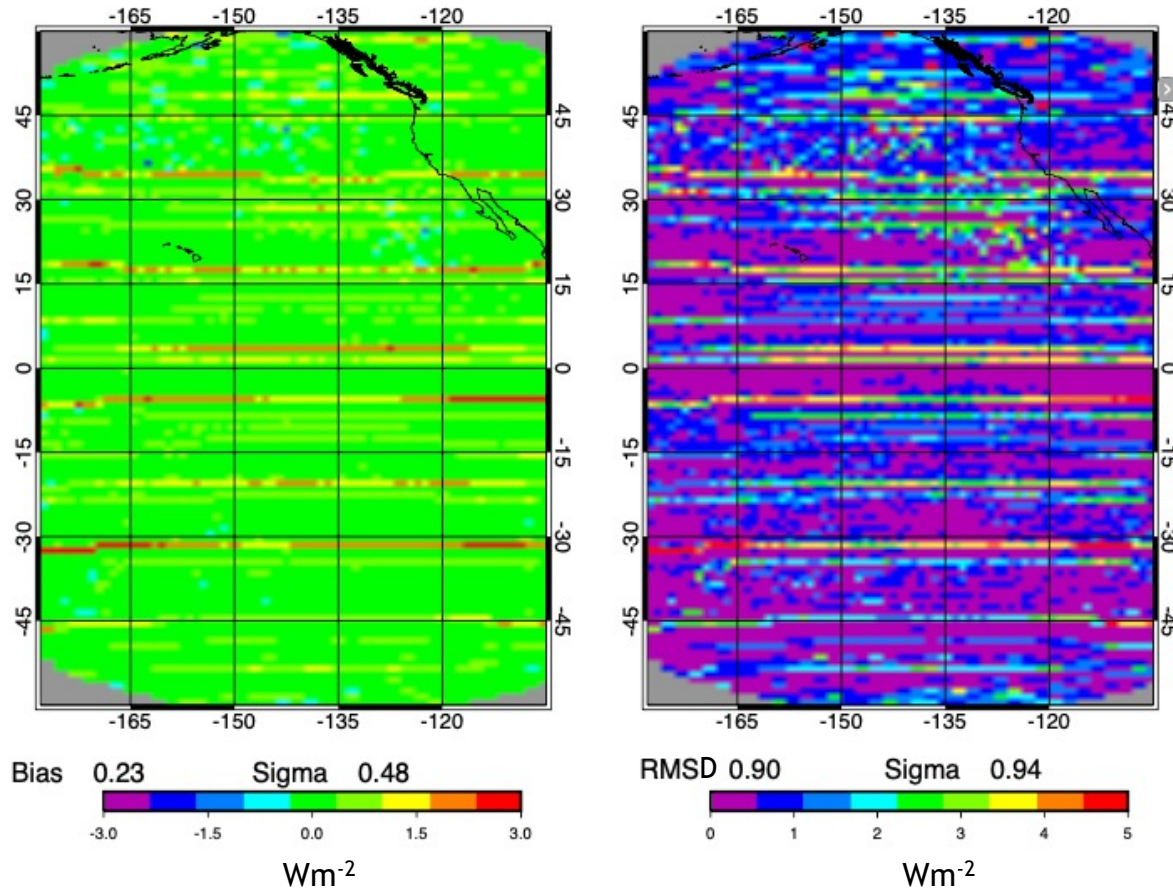
CNN Cleaned and Human Cleaned are in better agreement

Feb 2021 TOA Longwave Up Flux: 13:30 UTC Average
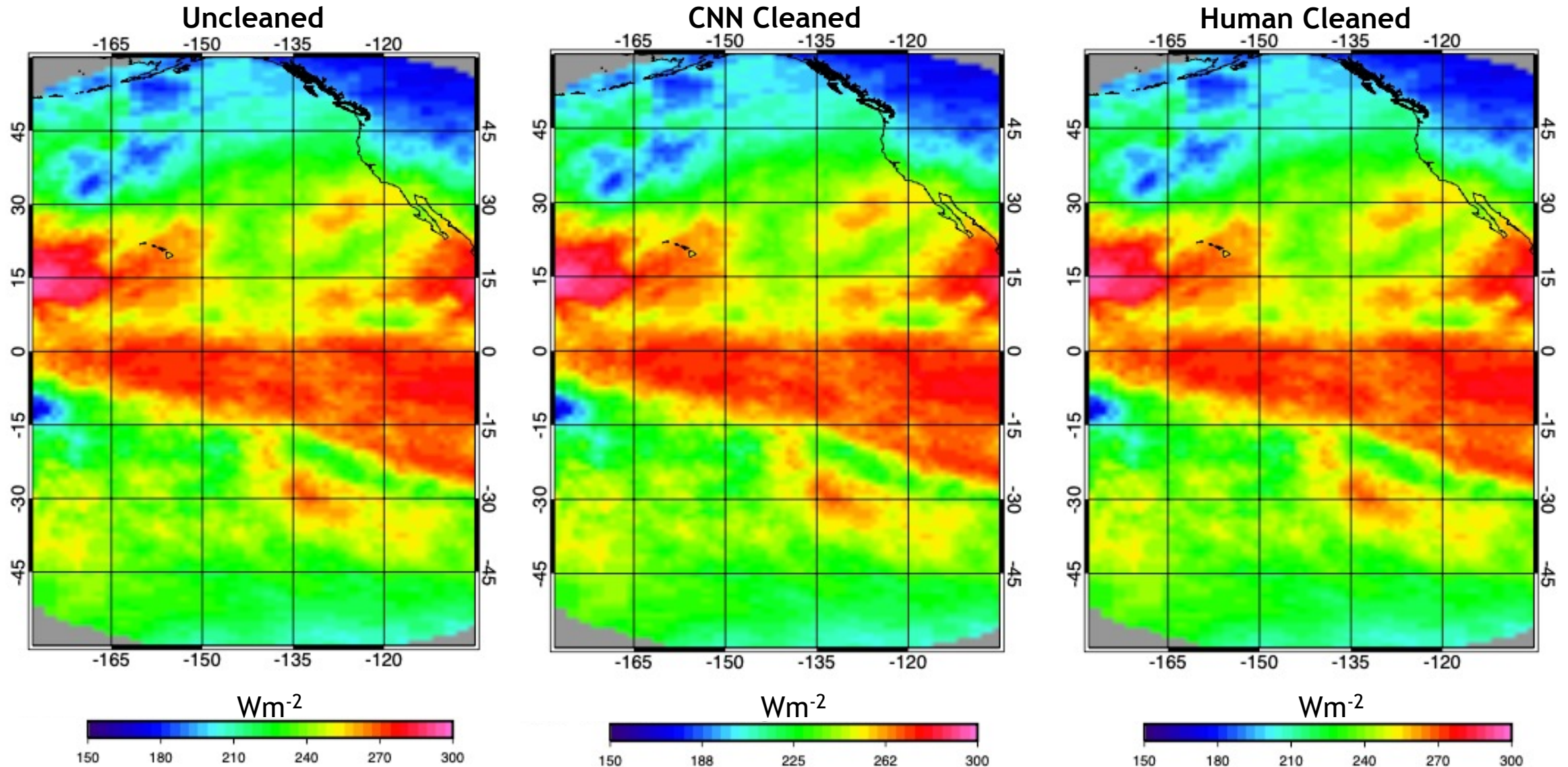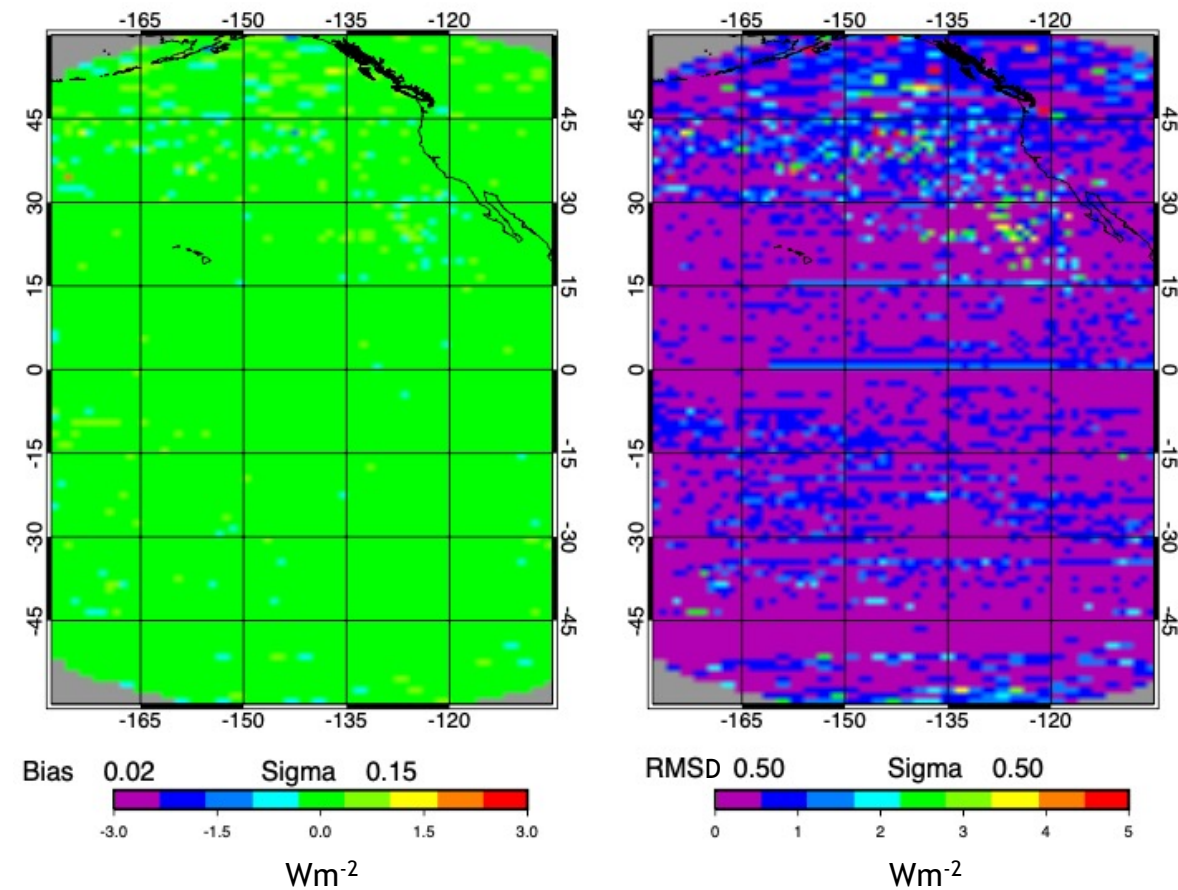
Feb 2021 TOA Longwave Up Flux: 13:30 UTC Regional Differences

CNN Cleaned – Uncleaned

CNN Cleaned – Human Cleaned

Bias 0.23   Sigma 0.48

Wm⁻²

RMSD 0.90   Sigma 0.94

Wm⁻²

Bias 0.02   Sigma 0.15

Wm⁻²

RMSD 0.50   Sigma 0.50

Wm⁻²

Differences less striking than those with cloud products, but CERES is a flux product and these biases and degrees of daily variance matter

CNN vs. Human Summary

Cloud Effective Pressure (hPa)	Mean				Daily Variance			
	CNN–Uncleaned		CNN–Human		CNN–Uncleaned		CNN–Human	
UTC	Bias	Std	Bias	Std	RMSD	Std	RMSD	Std
10:30	0.37	3.05	0.17	2.33	3.7	10.7	3.3	8.2
11:30	1.06	4.59	0.48	2.62	6.7	16.8	4.9	10.7
12:30	3.77	9.04	0.90	3.18	14.3	26.1	6.3	12.5
13:30	5.33	10.59	0.93	3.79	17.8	28.4	8.7	15.2
14:30	2.27	6.33	0.65	2.45	9.2	19.5	4.8	10.0
15:30	0.52	2.76	0.30	1.64	3.1	10.7	2.5	7.1
16:30	0.27	2.37	0.15	1.39	1.9	8.9	1.6	6.1

TOA LW Up Flux (Wm^{-2})	Mean				Daily Variance			
	CNN–Uncleaned		CNN–Human		CNN–Uncleaned		CNN–Human	
UTC	Bias	Std	Bias	Std	RMSD	Std	RMSD	Std
10:30	0.01	0.16	0.01	0.16	0.36	0.49	0.37	0.50
11:30	0.01	0.18	0.01	0.18	0.42	0.54	0.41	0.54
12:30	0.15	0.41	0.02	0.15	0.70	0.81	0.44	0.46
13:30	0.23	0.48	0.02	0.15	0.90	0.94	0.50	0.50
14:30	0.08	0.27	0.01	0.10	0.49	0.66	0.32	0.39
15:30	0.01	0.06	0.01	0.06	0.18	0.29	0.17	0.29
16:30	0.00	0.05	0.00	0.05	0.11	0.23	0.11	0.23

61% decrease in cloud pressure bias

33% decrease in cloud pressure variance

38% decrease in LW flux bias

17% decrease in LW flux variance

CNN and Human Cleaning Efforts are more consistent

Conclusions

Skill of CNN cleaning on validation set is good despite training curation shortcomings

CNN and human cleaned cloud products look natural – appear nearly identical

CNN and Human cleaned Flux products results align closer than either with Uncleaned

CNN effective at identifying and removing GOES-17 scanline anomalies

At least as effective as human cleaning but with significantly less effort

In operation for GOES-17 as of the Fall 2022 Eclipse Period
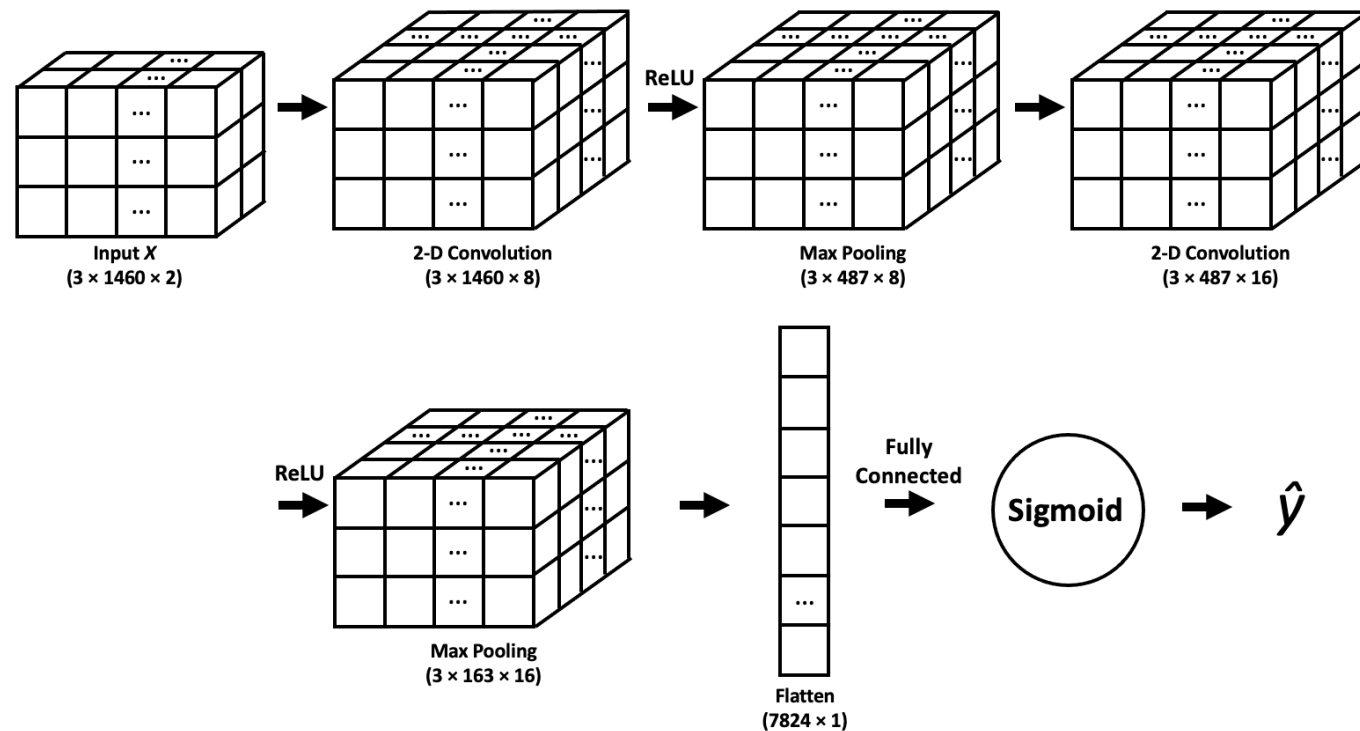
Backup Slides

Training the CNN

Randomly (by whole scans) separate predictor → label pairings into training (70%) and testing (30%) sets

Feed predictors and labels into CNN and make prediction

Evaluate prediction skill

	Validation
Recall	0.82
False Alarm Ratio	0.28
False Alarm Rate	0.01
Critical Success Index	0.55
Heidke Skill Score	0.70

Some Variance between Training and Testing – but overall excellent skill

Skill tied to consistency and thoroughness of curated training set

Input X
($3 \times 1460 \times 2$)

2-D Convolution
($3 \times 1460 \times 8$)

ReLU

Max Pooling
($3 \times 487 \times 8$)

2-D Convolution
($3 \times 487 \times 16$)

ReLU

Max Pooling
($3 \times 163 \times 16$)

Flatten
(7824×1)

Fully Connected

Sigmoid

$\hat{y}$

Application

- Apply CNN parameters to every 3×N subset of X input
  - 1 Feb – 28 Feb 2021
  - 10:30 – 16:30 UTC hourly processing timestamps

- Determine ŷ for each 3×N subset image

- Produce three version of the CERES SYN1deg Ed4 product February 2021
  - Uncleaned
  - Human Clean
  - CNN Cleaned

- Compare 1° gridded hourly retrievals, averaged for the month
  - Cloud top pressure
  - TOA LW Upward flux

CNN vs. Human Cleaning

CERES Ed4 GOES-17 Cloud Phase: 2021 054 15:30 UTC

Human Cleaned
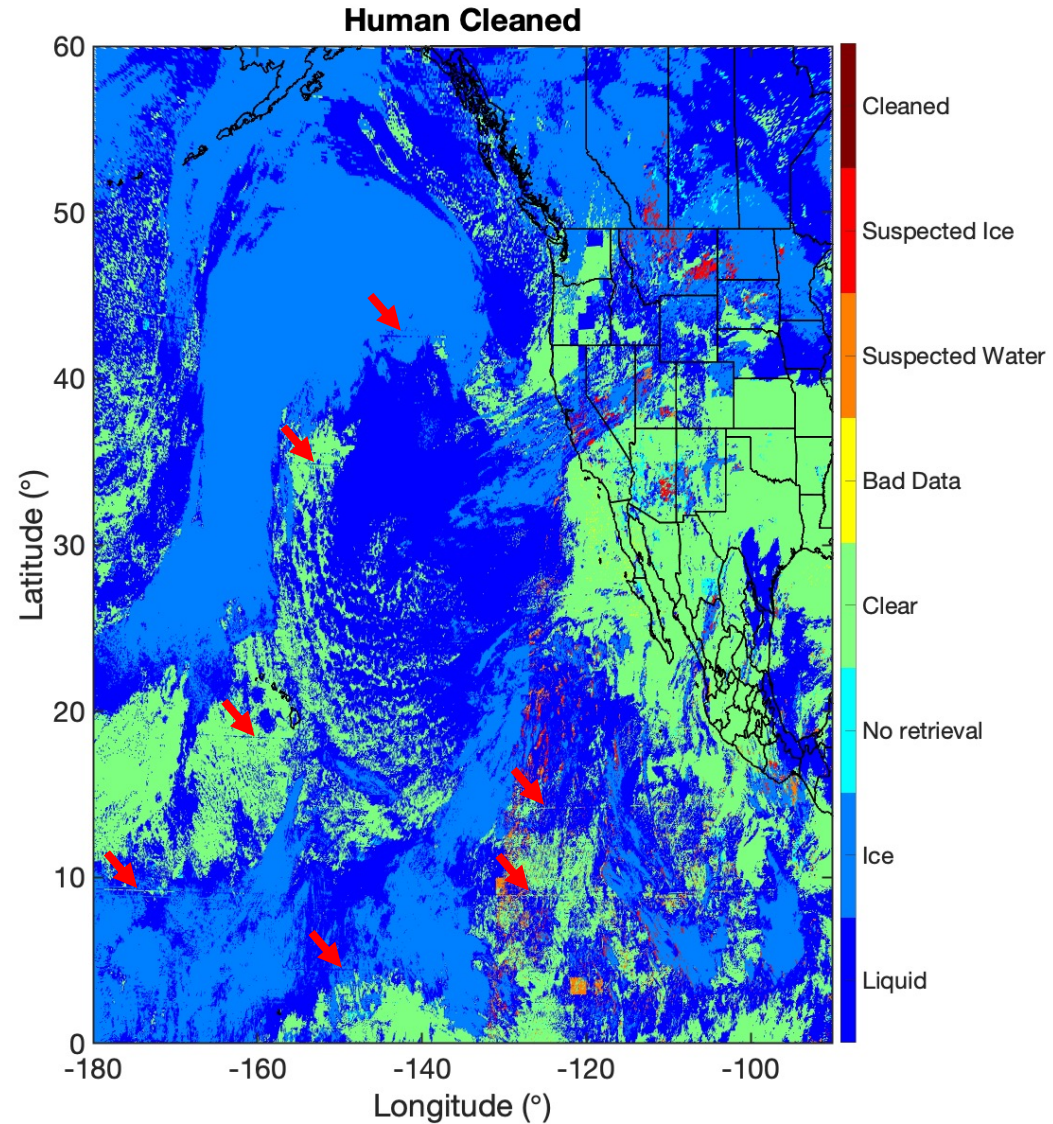
Feb 2021 Cloud Top Temperature: 13:30 UTC Average

Uncleaned

CNN Cleaned

Human Cleaned